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Research Technical Paper

Quantifying the Impact of Oil Prices on Inflation

Colin Bermingham *

Economic Analysis and Research Department
Central Bank and Financial Services Authority of Ireland
P.O. Box 559, Dame Street
Dublin 2
Ireland
http://www.centralbank.ie

*The views expressed in this paper are the personal responsibility of the author. They are not necessarily held either by the CBFSAI or the ESCB. The author would like to thank Antonello D'Agostino, Kieran McQuinn, Derry O' Brien, Gerard O' Reilly and participants at an CBFSAI seminar for their comments. All errors are my own. Email: colin.bermingham@centralbank.ie

Abstract

The substantial increase in oil prices over the past six or seven years has provoked considerable comment within the international media. While this increase has not had quite the same impact as that experienced in the 1970's, the magnitude of the price increases still has significant implications from a macroeconomic perspective. This is particularly the case in terms of inflation. The re-emergence of the oil price issue necessitates a re-examination of econometric estimates of the influence of oil prices on inflation. We examine this issue in the case of a small open economy - that of Ireland.

Non Technical Summary

The generally benign inflationary environment experienced in most developed countries since the mid eighties is now under threat. One cause for this has been the sustained increase in the price of oil. In the past five years, there has been a four-fold increase in the price of oil denominated in US dollars. This has had a significant effect on inflation internationally. Interestingly, however, the effects of the recent oil price increases have been less damaging to economic growth and less inflationary than those experienced during the oil price crises of the 1970's. This issue has already received some academic interest as it suggests that our econometric estimates of the pass-through from oil prices to inflation need to be re-visited.

This paper investigates a related problem, which is whether it is possible to forecast the energy component of inflation using oil prices in the Irish case. The Irish situation provides an interesting case study because it typifies the case of a small open economy. In terms of forecasting the impact of rising oil prices on inflation, there is one potential complication in the sense that commodity prices, such as food, have also witnessed considerable increases. Using standard approaches, it is difficult to disentangle which part of an increase in inflation is due to higher oil prices and which part is due to higher food prices. To address this problem, we focus only on the energy component of overall inflation in the estimates. Clearly, food price increases are not going to impact on the energy component of inflation so any estimates of the impact of higher oil prices on the energy component are not capturing higher food prices. In addition, the energy component used in the paper excludes regulated prices so that the series under examination represents the prices of the purely market-driven components of energy.

Using a simple regression based forecasting technique, it is possible to construct forecasts that are more accurate than those generated by a standard benchmark model. This is a notable feature in itself as, ironically, in the recent forecasting literature, standard benchmark models frequently outperform more sophisticated approaches. In the paper, forecasts are constructed for up to three months in the future. This is a relatively short forecast horizon but accurate energy forecasts are extremely difficult to generate over even moderate time horizons due to the volatility of oil prices. Thus, the focus on a three-month forecast horizon represents a realistic target. The improvements in forecast accuracy relative to the benchmark range from 20% to 33% at the one-month horizon and from 9% to

26% at the three-month horizon. This represents a meaningful improvement in forecasting power. If the price of refined petroleum products is used in place of crude oil in estimation and forecasting, it is possible to gain further improvements in forecast accuracy in certain cases.

The final issue considered in the paper is how to construct forecasts of the energy component of inflation for up to a year in the future. There is considerable uncertainty regarding forecasts of this type as it is necessary to use some forecast of oil prices for the year ahead. For the first long-term forecast, the future path of oil is taken from futures market, which implies that the price of oil will remain over $140 per barrel for next year. This forecast implies an increase in energy inflation over the next couple of months with a fall back in inflation at the end of the year. However, in this scenario, energy price inflation would still be about 9% by May 2009. In an alternative scenario, in which oil prices were assumed to fall back slowly to $100 per barrel by December 2008, the energy inflation rate would still be strong for the remainder of 2008 but would decrease to approximately 2.4% in May 2009. This demonstrates how sensitive the long-run forecasts are to the assumed future path of oil.

1 Introduction

The observed reduction in the volatility of macroeconomic variables in developed economies, commonly referred to as the "Great Moderation", has been well documented. The salient features for these economies has been low, stable inflation and consistent economic growth. The stability of inflation is now under serious threat. Inflation has been on the rise in developed economies following persistent increases in the prices of oil and agricultural commodities. The impact of oil prices on inflation, in particular, has re-emerged as a key macroeconomic issue. During 2003, oil traded between $28 and $36 per barrel but by May 2008, this had increased to almost $125 per barrel. This has had a significant effect on inflation internationally.

To quantify the impact of oil prices on inflation, consider figures released by Eurostat on euro area inflation. The Harmonised Index of Consumer Prices (HICP) is a pan-European measure of inflation. Amongst others, it is calculated for the individual countries of the EU and for the Euro Area as a whole. Eurostat also produce a core measure of the HICP which excludes energy prices. The difference between the headline rate and the core rate is the contribution of the energy component to the headline rate. The HICP inflation rate for the Euro Area in May 2008 was 3.7%. The inflation rate excluding energy was 2.6%. Thus, the contribution of the energy component was 1.1%, meaning that roughly one third of overall inflation was attributable to energy. Clearly, the energy component is one of the most important contributors to the overall inflation rate in the current climate. The impact of energy price developments on inflation is easy to quantify after the fact however. The key question this paper aims to address is whether it is possible to construct forecasts of the energy component based on current oil price developments.

To answer this question, we consider the case of Ireland. Ireland represents the archetypal case of a small open economy. In 2007, the sum of imports and exports was equivalent to 148% of GDP, meaning that, as a highly open economy, Irish inflation rates are significantly affected by international developments. The Irish inflation rate has been pushed higher by international oil and food prices in the same way as other European economies. In the European context, the value of the euro against the dollar has also increased significantly. In the Autumn of 2002, the euro and dollar were broadly equal in value. From March 2008 until July 2008, representing the last five months of data, one euro has rarely traded below one dollar and fifty five cents. The strength of the euro has insulated countries within the

Euro Area from the full effects of the recent oil price spikes but these economies have still experienced considerable energy inflation.

The approach taken in this paper is purely empirical. The aim is to find a modelling approach that is optimal from a forecasting perspective. Forecasts are constructed for three months into the future, as model-based energy forecasts are extremely poor at even medium term horizons. However, in order to compute forecasts of the energy component over longer horizons, data on oil price futures are used to condition forecasts from the short-term forecast models. The energy component is broken down into its constituent parts and stripped of administered price series. Administered prices are the prices of items that are either fully or partially regulated. In the context of the Irish energy component, this refers to the electricity and piped gas series. By excluding these series, we have a more refined measure of energy inflation that is determined purely by market forces. This will be referred to as the Non-Administered Energy (NAE) series.

The constituent items in this series are forecast using two econometric methods. For each method, these individual forecasts are then combined to construct a forecast of the NAE series. The same forecasting methods are also applied directly to the NAE series. There are gains to be made from forecast aggregation but only over the shortest of forecast horizons. Using standard benchmark forecasts, it is possible to improve on the benchmark model for all forecast horizons. Reductions in the Root Mean Squared Error (RMSE) of the model forecasts relative to a benchmark range from 20% to 33% at the one-month horizon and from 9% to 26% at the three-month horizon. This represents a significant improvement in forecasting power. The paper also considers whether it is possible to improve forecast accuracy further by using the price of refined oil products rather than crude oil prices. Although there is not a universal improvement in forecast accuracy, there are meaningful improvements in certain cases.

2 Inflation in an Irish Context

Energy price inflation has rarely been out of the business pages over the last three years. To put the oil price increase in context, Figure 1 graphs the price of a barrel of oil, which is priced internationally in US dollars, over the last eleven years. The more relevant measure of oil prices in Ireland is the euro price of oil so the graph also includes this series. It can be seen that the dollar price of oil, denoted in blue, has increased more rapidly than the euro price over the last five years as the strength of the euro has insulated those within the euro system from the full impact of the oil price increase. Despite the mitigating effect of these currency movements, there has still been considerable energy price inflation. Figure 2 graphs energy price inflation over the last five years. Over this period, year-on-year energy price inflation has generally been significantly higher and more volatile than overall inflation. Energy price inflation in May 2008 recorded an annual increase of 9.2% whereas the overall HICP rate was 3.7%. The annual average year-on-year change in the energy component was 12.6% in 2005, which was the largest recent annual change.

The impact on overall inflation of these energy price changes can be seen by examining the difference between overall inflation and inflation excluding the energy component. Figure 3 graphs inflation in black, inflation excluding energy in blue and the difference between the two, which is the contribution of the energy component to overall inflation, in green. The contribution of energy inflation to the overall inflation rate peaked in October 2005. The inflation rate was 2.64% and energy accounted for 1.42% of this, meaning that over half the overall inflation rate in that month was attributable to energy. Over 2005, inflation averaged 2.17% while the average energy contribution was 0.87%, a contribution of nearly 40% on average over the year. Given the importance of the energy component of inflation, it is critical to have a clear understanding of the impact of oil price changes on energy inflation.

The weight of the energy component in the HICP is approximately 8.7% for Ireland. This is slightly higher than its weight of 7.8% in the CPI as the HICP is a smaller basket of goods and services. The composition of the energy components in the HICP and CPI are identical however. Thus, although the focus of this paper is the HICP, the results are equally valid with respect to the CPI energy component. In this paper, the energy component is split into its constituent parts. The first column in Table 1 shows the current weights of the various elements that constitute the energy component. The exact weight of each item and the mix of items in the component changes every five years when the CPI is rebased but changes to the make-up of the energy component over the last fifteen years have been fairly minor.

Unleaded petrol and diesel together account for approximately 48% of the energy component, but with petrol having a weight almost four times that of diesel. Home heating oil is referred to as fuel oil in this paper - this is how it is referred to in the HICP basket by our statistical agency. It accounts for 11% of the index. These three items are all heavily influenced by oil price developments. Other items generally used for home heating such as coal, turf, briquettes and fire-lighters together account for under 10% of the energy component. Electricity is an important item, with a weight of 20%. Of the two gas components, piped gas, at about 10% of the index, is much more important than bottled gas, which only has a weight of 1.5%. However, piped gas and electricity prices are both regulated and change price only occasionally and in discreet jumps. As they do not respond in a predictable way to international energy prices, they were excluded from the current energy component in order to form a new market driven component. This removed approximately 30% of the weight of the official energy component. The second column of Table 1 shows the weights of the NAE series once the remaining items are rescaled following the removal of the administered price series.

3 Modelling and Forecasting Inflation

3.1 Review of Literature

The paper is primarily a forecasting paper, which estimates the impact of oil prices on inflation. There is an existing literature that aims to quantify the impact of oil prices on key macroeconomic variables such as output and inflation. Amongst others, Hamilton (2008) notes that nine out of ten US recessions since World War II were preceded by a spike in oil prices. A number of studies discount the possibility that the relationship between oil prices and output is merely a statistical coincidence.[1] In the past surging oil prices have stalled growth and employment but stimulated inflation, the combination of which is referred to as stagflation. Thus, the potentially ruinous effects of rampant oil prices are already well documented.

One of the most active research areas of late is in attempting to explain why current oil price increases have not had the same impact on the world economy or national economies as the oil price shocks of the 1970's. The most common explanations are the decreased oil intensity in production and the general low inflationary environment.[2] This change in the

[1]See Hamilton (1983), Rotemberg and Woodford (1996) and Carruth et al (1998) for example.

[2]See Chen (2008) and Gregorio et al (2007) for example.

reaction of national economies to recent oil price shocks relative to earlier shocks suggests that econometric estimates gauging the impact of oil need to be revised and updated. This paper estimates the inflationary impact of oil prices in the Irish context. The impact for Ireland reflects that of other small open economies although the precise quantitative estimates will vary according to the dependency of each country on its oil imports. Relative to larger, less open economies, in which domestically generated inflation is of more importance, one would expect the inflation rate in Ireland to be more responsive to changes in oil prices. Standard econometric models are used in the analysis but the approach is non-standard in a couple of respects. We now outline some of the paper's contributions.

Models that aim to predict the inflationary impact of oil prices typically focus on the aggregate inflation rate. However, there are always other factors at work in the economy that could potentially offset the effects of oil. For example, the significant increase in agricultural commodity prices being experienced through 2007/2008 could, if not properly controlled for, be mistaken for oil price inflation. The approach in this paper is to examine the impact of oil prices on the energy component in isolation. In addition, regulated prices are cleansed from the energy component to give a purely market driven measure of energy inflation. This is a simple solution to isolating the exact influence of oil on the inflation rate but one which is not adopted in the literature. Solely quantifying the effect of oil prices on this measure of inflation only is to the criticism that second round effects are ignored but there is limited evidence of second round effects to date. Second round effects refer to the situation where oil price increases lead to general inflation in other sectors of the economy through increased production costs. Some second round effects have been seen in the transport sector, particularly in the airline industry. There has also been an increase in some regulated prices but these cannot be modelled econometrically. Outside the energy and food sectors, inflation in other sectors is not running significantly above historical levels, suggesting limited evidence of second round effects.

Accurate medium term forecasts of inflation are notoriously difficult to generate. This is reinforced by the vast array of models that fail to beat standard benchmarks at even moderate time horizons. Atkeson and Ohanian (2001) found that Philips curve models could not consistently beat a naive benchmark forecast of overall inflation. Stock and Watson (2006) point out that "the improvement of standard multivariate forecasting models, such as the backward-looking Philips curve, over a univariate benchmark has been less in percentage terms since the mid-1980s than before". Thus, the difficulty in beating standard benchmark inflation forecasts using multivariate models has increased. Accordingly, a naive benchmark which forecasts no change in the inflation rate is adopted in this paper. However, as naive benchmarks are mainly used in relation to aggregate CPI inflation, which tends to be more persistent and less volatile than the inflation rate of the energy component, this paper also considers a second benchmark in the form of a autoregressive forecast.

The approach taken to forecasting Irish inflation has been quite varied in terms of the technical tools used but a key unifying theme in the literature is the recognition that the open nature of the economy is a critical factor in the determination of Irish prices. Slevin (2001) notes that the output gap, which is a purely domestic measure, is not sufficient to explain Irish inflation. Kenny and McGettigan (1996) and Slevin (2003) both use small open economy models, in which there is a distinction between the traded and non-traded sectors, in explaining Irish inflation. Kenny and McGettigan (1996) also model imports prices specifically using an exchange rate pass-through model. Bermingham (2007) calculates a core inflation measure taking account of the role of oil prices and uses the core measure to forecast HICP inflation. This paper, however, is the first to focus explicitly on the energy component of inflation in a forecasting context.

3.2 Data

The data used in the study are monthly. Oil prices refer to the price per barrel of crude oil denominated in US dollars and are available from the IMF. These were converted to euro using average monthly exchange rates. The price series for the constituent energy components were constructed by chain-linking these series across three CPI base periods. The NAE series was then constructed using these series. These series are available from December 1996 - May 2008, which results in a sample of 138 data points prior to any variable transformations. The refined prices used in the paper are the Rotterdam gasoline and diesel prices. These series are available daily but monthly averages were again taken for this paper.

4 Empirical Approach

Two forecasting models are used in the paper. These forecasting methods are applied to the aggregate NAE energy component. They are also applied to the individual items in the component and the forecasts are aggregated to arrive at a second candidate forecast for the energy component. This aggregation procedure is carried out for both forecasting models. It is found that there are gains to computing individual forecasts and then aggregating the forecasts. However, these are greatest at the one-month time horizon. Of the eight items in the NAE series, only three are forecast individually and naive forecasts are used for the remaining five. Models are used to forecast petrol, diesel and fuel oil. The only data used to forecast these series are the series themselves and oil prices. Naive forecasts are made for firelighters, coal, turf and briquettes, motor oil and bottled gas. The items which are forecast using the naive approach account for only 16% of the NAE series. Some items are not forecast because of their small weight in the index and others because they have no relationship with oil prices. Direct forecasts are also constructed using the prices of refined oil products as the inputs to the estimation and forecast procedure.

4.1 Forecast Benchmark

The first benchmark forecast is a naive benchmark and will be referred to as the AO benchmark in the remainder of the paper. The forecast horizon is three months. The benchmark forecast is for no change in the current inflation rate. For example, if yearly energy inflation is 4.5% for June 2005, the benchmark forecast for each month for July 2005 - September 2005 is also 4.5%. The literature mentioned previously confirms that it can be difficult to beat this a naive benchmark in many instances. The second benchmark considered is a simple autoregressive model. Forecasts are performed on a recursive basis. The first sample period for recursive estimates is December 1996 - March 2005. Models are estimated over this time frame and forecasts for April 2005 - June 2005 are computed. One month is added to the sample and the process is repeated. In this way, 36 sets of forecasts at the three month horizon were computed for each method. Forecasts are evaluated using the Root Mean Square Error (RMSE), a standard approach in the forecasting literature.

4.2 Modelling Strategy

The strategy used to model the NAE inflation series and its constituent parts is based on the strong observed co-movements between these price series and oil prices. Figure 4 depicts oil price inflation and inflation of the NAE component. The similarity in the behaviour of the two series is striking, with movements in oil price inflation tending to lead those in energy inflation with a small lag. On further inspection, it is clear that the individual items in the energy component display the same patterns. Figure 5 graphs oil price inflation and inflation in petrol, diesel and fuel oil inflation. The final part of the graph shows bottled gas inflation and international gas price inflation. Petrol, diesel and fuel oil prices are clearly driven by international oil price developments. Again, oil prices seem to demonstrate a leading relationship. Having uncovered a strong relationship between oil prices and energy inflation rates at both an aggregate and disaggregate level, the obvious question is whether it is optimal to forecast the individual components or instead the aggregate series. We consider both alternatives.

Prior to the discussion of the models used, let us first establish the stochastic properties of the data. As is typical, all the price series are non-stationary - results of unit root tests are not presented for this in the interests of brevity but are available upon request from the author. The inflation rates of oil and the energy components are all stationary. The results of the unit root tests are presented in Table 2. The tests are for the year-on-year growth rates. The unit root test used was the standard Augmented Dickey-Fuller (ADF) test. The critical value for this test at the 5% level given the sample size is -2.88. For all variables, the test statistic comfortably exceeds the critical value and so the null of a unit root is rejected for all the inflation rates considered.

Moving to the estimation strategy, the first model used is a standard pass-through equation in the form of an Autoregressive Distributed Lag (ARDL) model. In this set-up, the inflation rate of a certain item is regressed on past values of itself and past oil price inflation:

$$\pi_t = \alpha_0 + \sum_{i=1}^{n} \beta_i \pi_{t-i} + \sum_{i=1}^{n} \theta_i oil_{t-i} + \epsilon_t \tag{1}$$

This type of equation was fitted to the NAE series and to its components. Generally speaking, it was found that two lags for each variable fit the data and produced the best forecasts although there is a slight variation for some series. The residuals from the estimated equations were tested for serial correlation. The presence of lagged dependent variables in the regression creates a bias towards a finding of no serial correlation with the Durbin-Watson statistic. The general LM test suggested by Godfrey (1978) and Breush (1978) is used instead. There is no evidence of serial correlation using this test for either the NAE series or any of its components.[3]

In order to generate the forecasts, past values of oil price inflation and the past inflation rate of the series are needed. At the one month horizon, the forecasts can be conditioned on actual observed data. Beyond this, earlier period forecasts of the inflation rate can be used to condition later forecasts. The following equations detail how the three forecasts are constructed in each recursive step, assuming two lags for both energy inflation and oil price inflation. A "hat" is used to denote a forecasted variable:

$$\hat{\pi}_{t+1} = \alpha_0 + \beta_1 \pi_t + \beta_2 \pi_{t-1} + \theta_1 oil_t + \theta_2 oil_{t-1} \tag{2}$$

$$\hat{\pi}_{t+2} = \alpha_0 + \beta_1 \hat{\pi}_{t+1} + \beta_2 \pi_t + \theta_1 oil_t + \theta_2 oil_{t-1} \tag{3}$$

$$\hat{\pi}_{t+3} = \alpha_0 + \beta_1 \hat{\pi}_{t+2} + \beta_2 \hat{\pi}_{t+1} + \theta_1 oil_t + \theta_2 oil_{t-1} \tag{4}$$

In the first forecast, actual data can be used for the two lags of both energy price and oil price inflation - there are no hats on the right hand side of Equation 2. In period $t+2$, the first lag needed to construct the forecast is from period $t+1$. The forecast of inflation constructed in the first forecast step is used as the first lag for energy price inflation in the second forecast. The second lag still refers to actual data. Thus, in the second forecast equation, we see that the first lag of inflation has a hat while the second does not. For oil prices, forecasts are constructed using the last available data points even though these don't technically represent the lag from period $t+1$. This approach is taken because it yields the most accurate forecasts. For Equation 4, the energy price inflation lags are themselves both forecasts, as indicated by the two hats, while oil inflation lags are again the last actual data points.

Having already established the stochastic properties of the price series, they were tested for cointegration with oil prices using the Engle-Granger method. The results are presented

[3] Results not reported but available upon request.

in Table 3. In each case, the test was based on a cointegrating vector with the named variable and international oil prices converted to euro. The variables all exhibit evidence of cointegration at the 5% level. Given this evidence, long-run equations were estimated for each pair of variables. Short-run equations including an error correction term (ECM) were then estimated and used to construct the forecasts. In contrast to the ARDL approach, some assumptions need to be made about the future path of oil when constructing the forecasts from this approach, as future values of the equilibrium error are needed. Two assumptions were tested - oil prices remain constant or oil inflation remains constant. The constant price assumption was found to generate slightly better forecasts so this is the assumption used.

5 Forecasts

5.1 Forecast Evaluation

The forecast methodologies described in the previous section are now evaluated. Table 4 presents the results of the different forecasting methods applied to the individual components and to the NAE series directly. The numbers in the table the RMSEs and each section of the table shows the errors for a specific component. In each section, the first two rows show the errors from the two benchmarks - the AO forecast and the autoregressive (AR) forecast. The third and fourth rows of each section show the errors for the ARDL forecast and the cointegration model forecast.

The first section presents the results for the NAE series, the market driven energy series constructed in the paper. The ARDL forecasts and the cointegration forecasts are more accurate than both benchmarks. Although the ARDL and cointegration models have similar forecast power, the cointegration forecasts are marginally more accurate at all forecast horizons. The improvements in forecasts power relative to the AO benchmark using the cointegration approach are 21%, 19% and 21% at the one, two and three-month forecast horizons respectively.

A similar picture emerges in the remaining sections of the table, which detail forecast performance for the three main components of the NAE series. For each component, the two econometric forecasts outperform the benchmark forecasts. In addition, the forecasts using the cointegration model are slightly more accurate than those of the ARDL model. Improvements in forecast power relative to the benchmark are greater at the shorter horizons. Using the cointegration approach, the one-month forecast of fuel oil is 33% more accurate than the AO benchmark whereas at the three-month horizon, the greatest improvement in forecast power is for the petrol forecast, which is 26% more accurate than the benchmark.

5.2 Assessing the Importance of Oil Prices

The importance of oil prices can be gauged by comparing the AR model and the ARDL model. The only difference between these two models is the inclusion of oil price inflation in the ARDL model. If oil prices are really helping to improve forecast performance, we would expect forecasts without the oil prices included to perform poorly. The results of this exercise are presented in Table 5. The table presents the ratio of the RMSE from a model including oil prices to a purely autoregressive model for the NAE series and for individual components. At all time horizons, this ratio is less than one indicating that oil prices are contributing to forecast performance. For the direct forecasts of the NAE series, forecasts are 18% more accurate at the one-month horizon and 14% more accurate at the two and three-month horizons when oil prices are included. As a general feature, the improvement in forecast accuracy is more pronounced at the shorter horizons given the short lag lengths in the model.

It is also possible to test more formally if the ARDL model produces forecasts which are statistically superior to those of the AR model which excludes oil prices. For this exercise, only direct forecasts of the NAE series are compared. If the model with oil prices has more accurate forecasts statistically, this is equivalent to saying that the difference between the two forecast errors is statistically significant. Given that we are only interested in an improvement in forecast power relative to the autoregressive model, the hypothesis test is one-sided. The mean squared error (MSE) is used in place of the RMSE in the test. As is suggested from their names, the RMSE used up to now is simply the square root of the MSE. The MSE from the two models is compared using a statistic that identically resembles a standard t-test. Under the null of equal predictive ability, the form of the statistic is given by:

$$H_0: \ \delta_1^2 - \delta_2^2 = 0; \ \ S = \frac{\hat{\delta}_1^2 - \hat{\delta}_2^2}{\left(\hat{V}/P\right)^{\frac{1}{2}}} \tag{5}$$

where δ_1^2 is the MSE from the null (autoregressive) model, δ_2^2 is the MSE from the alternative survey model, $\hat{V}$ is the estimated variance of the forecast differential series and P is the number of predictions or forecasts. Despite the familiar form of the test, there are two potential complications when calculating this statistic.

One possible complication arises from the fact that the series of forecast error differentials used to construct the statistic can be serially correlated. This is normally the case when forecasts are performed for horizons beyond one-step. The reason for this is that forecast periods overlap for multistep forecasts in consecutive recursive iterations. When serial correlation is present, the long-run variance needs to be estimated. Correcting for serial correlation by using the long-run variance and then using standard critical values is referred to as the Diebold-Mariano (1995) test. The long-run variance is calculated as the spectral density of the forecast differential series at frequency zero. The Newey-West non-parametric kernel estimator is used with the automatic bandwidth selection procedure suggested by Andrews (1991). The difference between the standard variance and the long-run variance is small in this application.

A second complication arises when the null model is a nested version of the alternative model. In this case, it can be seen that the autoregressive model is nested in the ARDL model - the ARDL model reduces to the autoregressive model when the coefficients on oil prices are restricted to zero. Assume the null to be true, so that the autoregressive model is the true model. In the ARDL model, there are additional estimated regression parameters. The values of these coefficients are zero in population. They will not be exactly zero in-sample due to parameter estimation error. When performing out-of-sample forecasts, the additional noise imparted in the forecasts from including parameters whose population values are zero means that the mean squared prediction error will be larger for the alternative model i.e. $\delta_2^2 > \delta_1^2$ so that the hypothesised difference in MSE, $\delta_1^2 - \delta_2^2 < 0$. This means that the test statistic is not centred at zero - it is centred in negative territory. Standard test statistics are based on distributions with a mean of zero.

There are a number of ways to correct for this problem. The correction used in this application, which is the easiest computationally, is based on Clark and West (2006 & 2007). They recommend re-centring the distribution at zero, using a correction based on the fitted values (forecasts). The specific correction depends on the form of the null model. Given the parameterisation of the null in this application, the adjustment term equals the mean squared forecast differential. This adjustment term is added to the numerator of the test statistic displayed above. Having carried out this adjustment, inference can proceed in the usual fashion using conventional, asymptotically normal procedures familiar from Diebold and Mariano. The results of this exercise are presented in Table 6. The table shows the test statistics under the null that the AR model and ARDL model have equal predictive ability. Statistics are presented for each forecast horizon and the 5% critical value is 1.645 in each case. The null is rejected at all time horizons indicating that the inclusion of oil prices to the basic AR model results in statistically significant improvements in forecast performance. The forecast errors from the AO benchmark are larger than those from the AR model. Thus, we can be relatively certain that the improvement in forecast accuracy relative to the AO benchmark is also statistically significant.

5.3 Forecast Aggregation

Turning to the issue of forecast aggregation, the individual forecasts from the two estimation techniques were combined with naive forecasts for the components that are not modelled explicitly to form a second forecast for the NAE series. The intuitive approach to combining the forecasts would be to take the weights in Table 1 and multiply them by the forecasted inflation rate for each item. Consider this calculation in the simple case in which an aggregate series x at time t is made up of just two different series, x_1 and x_2 with weights λ and γ respectively that are fixed from the base period. This represents the case of a Laspeyers price index such as the HICP in Ireland:

$$x_t = \lambda x_{1,t} + \gamma x_{2,t} \tag{6}$$

The inflation rate, π_{t+h}, of the aggregate between t and $t+h$ is defined as its percentage change:

$$\pi_{t+h} = \frac{x_{t+h} - x_t}{x_t} \tag{7}$$

$$
\begin{aligned}
&= \frac{(\lambda x_{1,t+h} + \gamma x_{2,t+h}) - (\lambda x_{1,t} + \gamma x_{2,t})}{\lambda x_{1,t} + \gamma x_{2,t}} \\
&= \lambda \frac{x_{1,t+h} - x_{1,t}}{\lambda x_{1,t} + \gamma x_{2,t}} + \gamma \frac{x_{2,t+h} - x_{2,t}}{\lambda x_{1,t} + \gamma x_{2,t}}
\end{aligned}
$$

The weighted average of the inflation rates of the two individual series is given by this expression:

$$
\lambda \pi_{1,t+h} + \gamma \pi_{2,t+h} = \lambda \frac{x_{1,t+h} - x_{1,t}}{x_{1,t}} + \gamma \frac{x_{2,t+h} - x_{2,t}}{x_{2,t}} \tag{8}
$$

Clearly, the two expressions are not equal. Thus, with a fixed weight price index, it is not the case that the weighted average of the inflation rates of the individual items is equal to the inflation rate of the overall index. This lack of additivity only relates to the change in the index and not to the level. In other words, the weighted average of the price level of the individual items does equal the price level of the aggregate. In order to aggregate, we use the forecasted inflation rates to generate a forecast of the weighted price level for each item, sum the weighted prices and calculate the implied inflation rate for the aggregate.

Table 7 presents the results of this exercise. The numbers in the table refer to the ratio of the RMSE from the disaggregate approach versus the aggregate approach. A value less than one again indicates that the combination of individual forecasts is more accurate than using the same approach to forecast the NAE series directly. The results for the ARDL approach show that forecast combination can improve forecasts at the one-month horizon by 7% relative to a direct forecast. At months two and three, the forecast errors are broadly similar using indirect versus direct forecasts. For the cointegration model, there is a 8% improvement at the one-month horizon, no difference at two months and a 3% improvement at three months. Overall, the results suggest some role for forecast aggregation, as the results are encouraging at the one-month horizon and, although the gains may be modest at other horizons, it is rarely the case that the combined forecasts are less accurate.

5.4 Refined Prices

In this section, we consider an alternative data source for the input to the forecasts. Specifically, data on the refined price of oil products is used in place of international crude oil.

The difference between the two can be thought of as the cost of refining crude oil into a product suitable for retail distribution. Refined prices for gasoline and diesel are available and these represent the prices that refineries charge retailers for gasoline and diesel. Although the price paid at the pump, and in turn reflected in the consumer price index, will also incorporate the profit margin of the retailer and any local taxes, the refined price is closer to the retail price than the price of international crude oil and may help in the construction of more accurate forecasts.

Direct forecasts of the NAE series and its components are constructed in the same manner as before. The refined price of gasoline is used as the input in the NAE and the petrol price forecasts while the refined price of diesel is used to construct the diesel and fuel oil forecasts. The results are presented in Table 8 and are analogous to those in Table 4. The first two rows of each section present the RMSE values for the benchmarks. These are identical to the numbers presented in Table 4 but are replicated here for convenience. As was the case with the forecasts based on crude oil prices, the refined price forecasts are more accurate than the two benchmarks considered at all time horizons.

If we compare the ARDL forecasts using refined prices in Table 8 to those using crude prices from Table 4, there are considerable improvements in forecast power at the one-month horizon for all items. The results are mixed at the two-month horizon. The forecasts for the NAE series and diesel are more accurate but petrol and fuel oil are less accurate. At the three-month horizon, only the forecast for diesel is more accurate. These results would appear to suggest that the benefits to using refined prices are confined to the short forecast horizons. However, for the NAE series, the improvements in forecast power at months one and two are quite large whereas the forecast at month three is only marginally less accurate, so the evidence in favour of using refined prices in the ARDL forecast of the aggregate NAE series is quite compelling.

For the cointegration model forecasts, there are some similarities in the results. At month one, all forecasts are more accurate when using refined prices relative to crude prices. At month two, the forecasts for the NAE series and for fuel oil are more accurate but petrol and diesel are less accurate while all forecasts using refined prices are less accurate for the three-month forecast. In Table 4, we saw that forecasts from the cointegration approach were generally more accurate than those from the ARDL approach. The reverse tends to be true with refined prices. Comparing direct forecasts of the NAE series using both econometric methods and both data types, one would favour the ARDL forecast with refined prices. Of all four methods, it has the most accurate forecasts for the first two months. The cointegration forecast with crude prices fares slightly better at month three but the ARDL with refined prices still has the best overall performance. The results suggest that forecast aggregation is unlikely to improve upon direct forecasts as the component forecasts are less accurate than the direct forecasts in the majority of cases.

6 Long-Term Forecasts

Despite the focus on short-term forecasts, in this section we generate long-term forecasts over a one-year horizon. Forecasting oil prices is now even more difficult than usual given their current volatility. The cause of the current oil price spike is difficult to attribute to any one cause. Many media commentators are pointing to the role of speculators as the driving force but this is disputed by others who maintain that fundamentals are driving the market. In this paper, the future path of oil is first taken from futures markets. The forecast is subject to a large degree of uncertainty which is the reason that short-term forecasts were favoured but the sensitivity of the forecasts to the oil price profile is examined by considering a second oil price path.

The data used in the estimation of the models ends in May 2008. Forecasts are constructed for June 2008-May 2009. A forecast of the exchange rate is also needed for the following year to construct forecasts and it is assumed that the euro/dollar rate remains unchanged. Actual oil price data are available for June 2008 but price data are not. June oil prices were noticeably higher than May and futures market data reflect this. The futures market profile for oil prices over the next year suggest that oil prices will stay over $140 per barrel. This price level is considerably higher than the recent data used in estimation. Oil broke $100 per barrel in February 2008 and had almost climbed to $125 in May. With futures suggesting over $140 per barrel for most of the forecast horizon, year-on-year forecasts conditioned on futures data suggest a sharp increase in energy price inflation for the next few months given that dollar oil prices are expected to be roughly twice the price they were in corresponding months last year.

Figure 6 graphs the forecast of the NAE series over the next year conditioned on oil remaining over $140 dollars per barrel. This oil profile suggests NAE inflation will peak at just under 17% in July before falling back to 14% in October and further back to under 9% in May 2009, the end of the forecast horizon. The NAE series represents approximately 6.1% of the HICP so at the forecasted peak of energy inflation in October, the NAE component will add just over 1% to the HICP inflation rate.

To examine the sensitivity of the forecast to the oil price assumption, a second more benign oil price assumption is considered. For this forecast, oil prices are assumed to fall slowly back to $100 per barrel by December 2008 and remain at that level for the remainder of the forecast horizon. This oil price profile is chosen arbitrarily for the sensitivity analysis. Figure 7 graphs the forecast of the NAE series in this case. The forecast of the series is quite similar to the previous forecast for the first six months of the horizon but NAE inflation falls much more rapidly in the second half of the forecast horizon. Indeed, under this assumption, NAE inflation is just 2.4% at the end of the horizon.

7 Summary and Conclusions

This study provides a means of quantifying the impact of oil price increases on inflation. The exercise is conducted within the context of a small open economy. Overall inflation rates, on an international basis, have been subject to two major influences over the past few years, that of oil prices changes and agricultural commodity price increases. To control for the impacts of agricultural commodity price increases on inflation, the approach adopted here is to focus on energy inflation and, in particular, a measure of energy inflation which is purely market driven. However, once the impact of oil prices on this component is known, it is trivial to calculate the impact on overall inflation.

In focusing on the energy component, this paper shows that simple econometric techniques significantly outperform standard benchmarks up to three months into the future. By forecasting the constituent parts of the energy series, the issue of forecast aggregation is also considered but gains in forecast accuracy are limited to the one-month forecast horizon. Beyond that, it is optimal to simply forecast the energy series directly. The paper also investigates whether the use of the price of refined oil products in place of the price of crude oil can improve forecasts. The results indicate that considerable improvements can be made at short time horizons, particularly in the case of the direct ARDL forecast of the energy series. The paper also constructs long term energy inflation forecasts for the next year and, as one would expect, these are quite sensitive to the assumed future path of oil prices.

There are a number of potential avenues for future work. At present, the forecast aggregation procedure only leads to benefits at the one-month horizon. Forecast models could be developed for the items which are presently forecast using naive methods. In addition, local taxes constitute a large percentage of the retail price of petrol and diesel in Ireland. By taking explicit account of this in the model set-up, further improvements in forecast accuracy may be possible. A further consideration is that the retail price of petroleum products may respond asymmetrically to price increases and price decreases. A model that takes allows for this could yield further dividends in terms of forecast performance although a longer time series of data may be necessary to consider this issue.

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Figure 1: Oil Prices Denominated in Dollars and in Euro

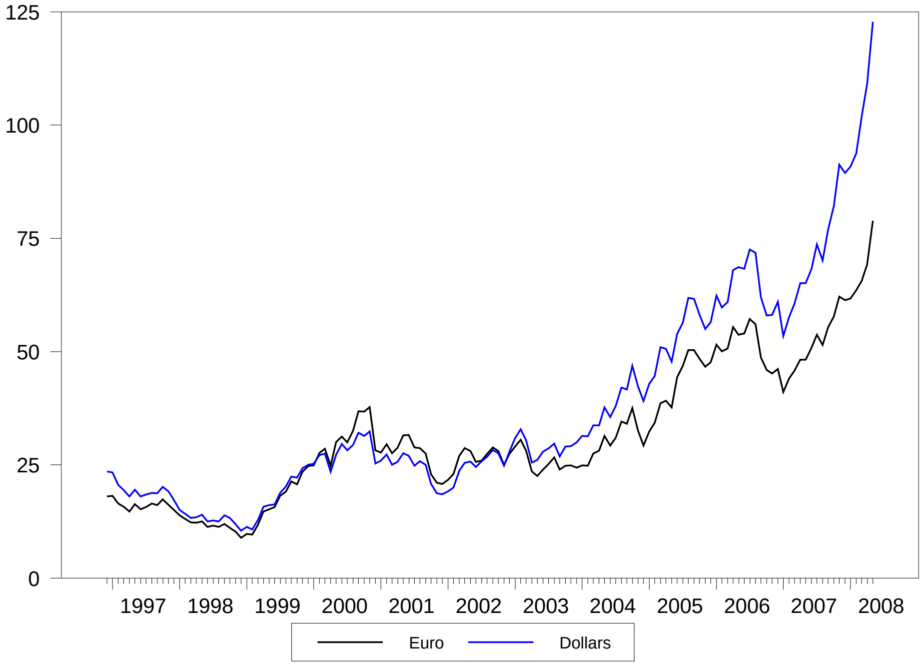

Figure 2: Recent Energy Price Inflation

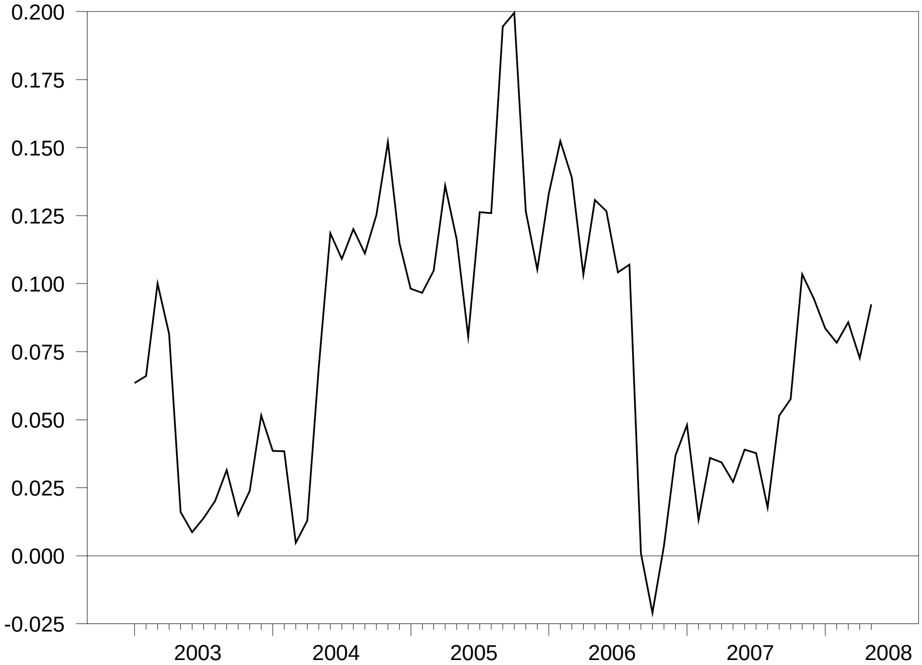

Figure 3: Inflation and Inflation Excluding Energy

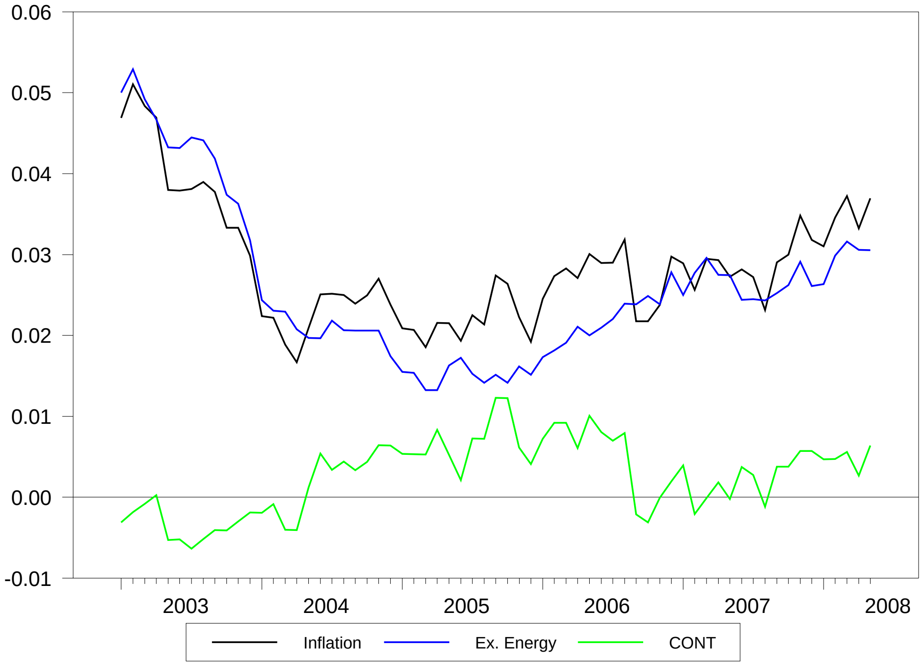

Figure 4: Oil Price Inflation and NAE Inflation

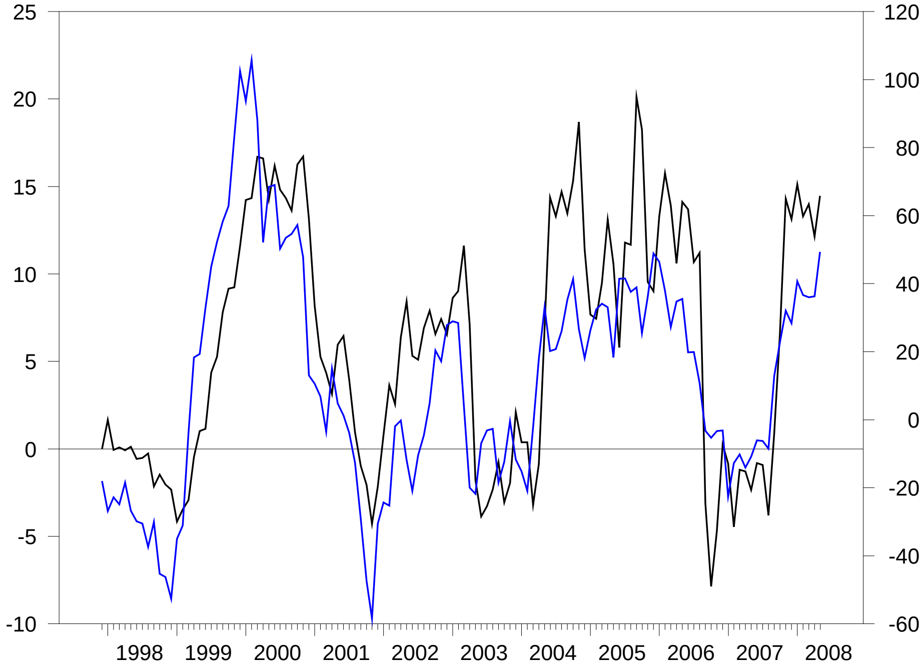

Figure 5: Energy Item Inflation and Commodity Prices

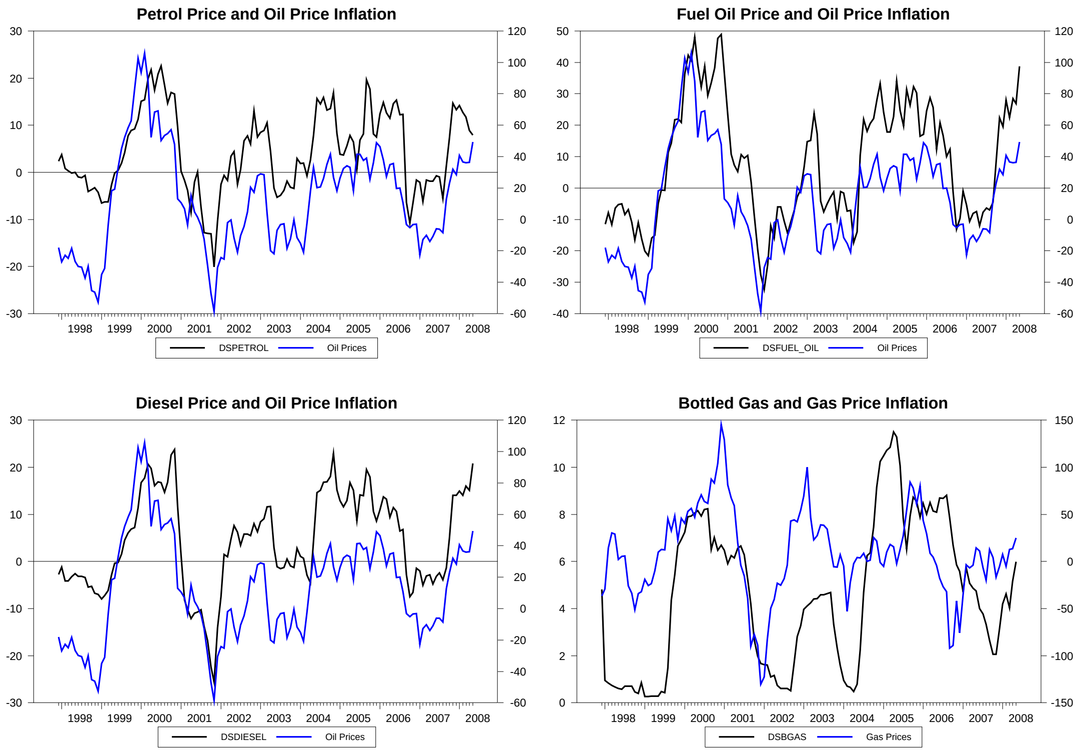

Figure 6: Forecast of NAE Series Inflation

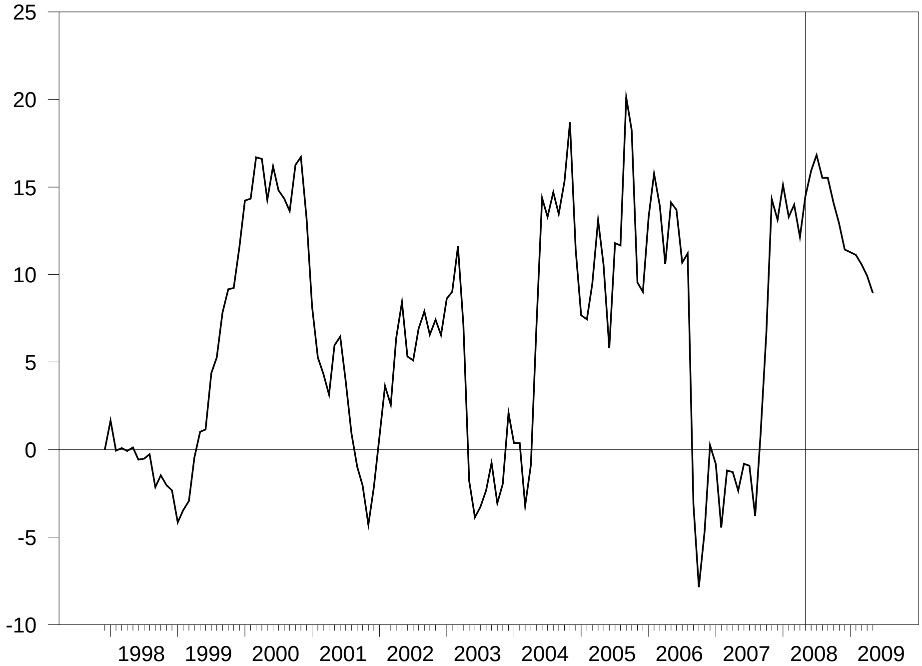

Figure 7: Alternative Forecast of NAE Series Inflation

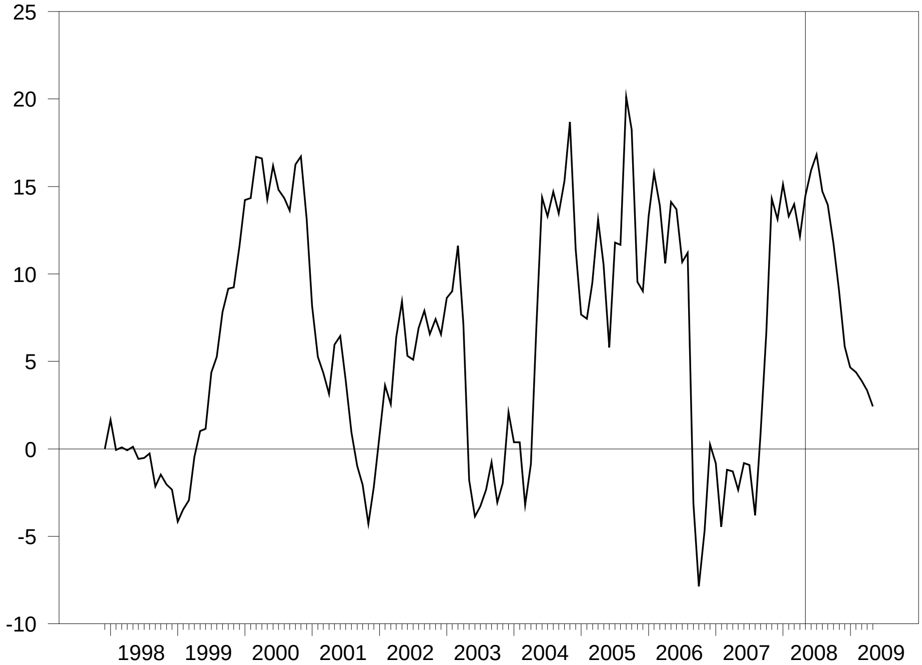

Table 1: Breakdown of the Energy Series

Item	Energy Weights	NAE Weights
Firelighters	0.63%	0.89%
Fire Handy Packs	0.12%	0.17%
Bottled Gas	1.52%	2.15%
Coal	4.42 %	6.28%
Piped Gas	9.74%	na
Electricity	19.89%	na
Fuel Oil	11.00%	15.63%
Turf and Briquettes	4.39%	6.24%
Petrol Unleaded	38.33%	54.46%
Diesel	9.79%	13.92%
Motor Oil	0.18%	0.26%

Table 2: Unit Root Tests

Variable	Statistic
Oil	-3.192^{+}
NAE	-3.3106^{+}
Petrol	-3.1324^{+}
Diesel	-3.0603^{+}
Fuel Oil	-3.4207^{+}

Note: The table tests the year-on-year growth rates of the variables in the Table for a unit root. + denotes rejection of the null hypothesis at the 5% level.

Table 3: Engle-Granger Cointegration Test

Variable	**Statistic**
NAE	-3.41^{+}
DIESEL	-4.57^{+}
PETROL	-5.11^{+}
FUEL OIL	-7.09^{+}

Note: The table presents results of tests to see if the named variables are cointegrated with international oil prices. Only two variables in each of the cointegration vector. Null hypothesis is that variables are not cointegrated. + indicates rejection of null at 5% level.

Table 4: Direct Monthly Forecasts of Energy Items

NAE	**Month 1**	**Month 2**	**Month 3**
AO	4.44	6.52	7.57
AR	4.33	6.29	7.12
ARDL	3.58	5.40	6.14
COINT	3.53	5.32	5.95
PETROL			
AO	5.20	7.75	9.09
AR	4.96	7.22	8.19
ARDL	4.10	6.42	7.16
COINT	4.05	6.25	6.75
DIESEL			
AO	3.83	5.77	7.02
AR	3.80	5.75	6.94
ARDL	2.89	4.74	6.34
COINT	2.90	4.76	6.28
FUEL OIL			
AO	7.55	10.13	11.79
AR	7.43	9.76	11.27
ARDL	5.40	7.98	10.73
COINT	5.03	7.69	9.81

Note: The table presents the RMSE for the benchmarks and the specified forecasting approaches.

Table 5: Contribution of Oil Prices to Forecast Accuracy

Method	**Month 1**	**Month 2**	**Month 3**
NAE	0.82	0.86	0.86
Petrol	0.83	0.89	0.70
Diesel	0.76	0.82	0.91
Fuel Oil	0.73	0.82	0.95

Note: The table presents the ratio of the RMSEs from the ARDL model to forecasts from a purely autoregressive model without lags of prices included. A value less than one indicates that the model with oil prices included is more accurate.

Table 6: Tests of Equal Predictive Ability

Series	**Month 1**	**Month 2**	**Month 3**
NAE	4.291	3.800	3.389

Note: The table presents the test statistic from the null hypothesis that the ARDL model and AR model have equal predictive ability. The 5% critical value is 1.645.

Table 7: Forecast Combination Results

Method	**Month 1**	**Month 2**	**Month 3**
ARDL	0.93	0.98	1.01
Cointegration	0.92	1.00	0.97

Note: The table presents the ratio of the RMSEs from disaggregate forecasts relative to forecasting the NAE series directly using the same method. A value less than one indicates that the combination of individual forecasts is more accurate.

Table 8: **Direct Monthly Forecasts with Refined Oil Prices**

NAE	**Month 1**	**Month 2**	**Month 3**
AO	4.44	6.52	7.57
AR	4.33	6.29	7.12
ARDL	2.90	4.71	6.23
COINT	3.19	5.26	6.91
PETROL			
AO	5.20	7.75	9.09
AR	4.96	7.22	8.19
ARDL	3.51	6.46	8.72
COINT	3.51	6.54	8.49
DIESEL			
AO	3.83	5.77	7.02
AR	3.80	5.75	6.94
ARDL	2.64	4.51	6.09
COINT	2.85	4.94	6.80
FUEL OIL			
AO	7.55	10.13	11.79
AR	7.43	9.76	11.27
ARDL	5.13	7.44	10.96
COINT	4.53	7.97	10.40

Note: The table presents the RMSE for the benchmarks and the specified forecasting approaches.